Machine learning-based dynamic risk measurement for white sugar futures under geopolitical risks

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Futures, as significant financial derivatives, play a crucial role in financial markets by fulfilling price discovery functions and providing efficient risk hedging tools. Against the backdrop of geopolitical conflicts, market risk emerges not only from external shocks and random fluctuations but also from strategic interactions among diverse participants including hedgers, speculators, arbitrageurs, and regulators. This study integrates traditional VaR theory with machine learning methods to systematically examine risk characteristics and transmission mechanisms in the sugar futures market under geopolitical uncertainty. Utilizing sugar No. 5 futures trading data from the Zhengzhou Futures Exchange spanning 2015−2019 and 2024, we employ a Random Forest model for feature importance analysis and compare three risk measurement approaches: traditional parametric VaR, historical simulation methods, and machine learning-enhanced VaR models. We conduct empirical tests to validate the theoretical relationship $\sqrt{3} \times \text{VaR}^T(1,p) \approx \text{VaR}^T(3,p)$ and calculate epsilon values (relative deviation between actual and estimated tail risk occurrences) through return tests. Annual delta values range between 0.26 and 1.16, averaging approximately 35% below theoretical values. The machine learning-based Value at Risk (VaR) at 95% confidence level exhibits a violation rate of 5.00%, demonstrating superior accuracy compared to parametric VaR (26.67%) and traditional historical VaR (7.00%). Epsilon values show no statistically significant difference between 2024 (0.08) and the 2015−2019 average level (0.14), indicating stable risk transmission mechanisms despite geopolitical conflicts. The hybrid "machine learning-traditional theory" risk framework developed in this research provides a theoretical foundation and practical guidance for regulatory bodies to enhance risk prevention and control systems, as well as for market participants to optimize risk management strategies. Despite geopolitical impacts, the fundamental risk transmission mechanisms of the sugar futures market remain relatively stable, demonstrating market resilience.

KEYWORDS

sugar futures, risk transmission, random forest, value at risk (VaR), machine learning

1 Introduction

Futures, as significant financial derivatives, play a crucial role in the financial markets by fulfilling the price discovery function and providing efficient risk hedging tools for various participants. These functions are inherently the result of strategic interactions among

diverse market participants, including producers, consumers, speculators, and arbitrageurs, who engage in game-theoretic behavior to achieve their individual objectives. This is achieved through features such as exchange margin systems, daily zero-net settlement mechanisms, and transparent contract rules. Since the establishment of the Chicago Mercantile Exchange (CME) in the 1920s, the futures market has rapidly expanded to encompass thousands of contracts across agricultural products, metals, energy, financial indices, and foreign exchange, thereby offering essential support for global commodity circulation and capital allocation. Within the agricultural futures market, sugar futures are particularly noteworthy due to their high trading volume, relative price stability, and strong correlation with livelihood demands. Sugar is not only a fundamental input for manufacturing and daily consumption but also a strategic reserve material for governments worldwide [1, 2], which establishes its importance for commodity risk analysis. Consequently, price fluctuations in sugar directly impact food security and economic stability.

In recent years, the frequency of geopolitical conflicts worldwide, such as the Russia-Ukraine conflict and localized disputes in the Middle East and Africa, has profoundly affected commodity prices and the stability of supply chains. These geopolitical risks alter the strategic landscape by changing the information sets, cost structures, and revenue expectations of market participants, thereby influencing their strategic interactions. These conflicts have posed significant challenges to the sugar futures market by causing supply chain disruptions, increasing production costs, and inducing severe price volatility. For instance, increased information asymmetry may intensify strategic interactions between informed and uninformed traders, while divergent expectations about conflict outcomes can lead to varied hedging and speculation behaviors. These developments not only heighten the trading risks for market participants but also have far-reaching implications for national macroeconomic policy formulation and food security strategies [3, 4]. Therefore, conducting an in-depth study of risk measurement and transmission mechanisms in the sugar futures market against the backdrop of geopolitical conflicts, with explicit consideration of the strategic interactions among heterogeneous agents, holds substantial theoretical and practical significance.

Existing research predominantly focuses on single approaches such as Value at Risk (VaR) models [5–8], historical simulation methods, or classical econometric techniques based on GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and EVT (Extreme Value Theory) to assess price risks in agricultural futures. However, these parametric methods often struggle to adequately capture tail risks or the interactions of multiple factors under intense market shocks and nonlinear transmission effects [9]. Moreover, they typically treat the market as a passive entity, ignoring the active strategic interactions between participants that can influence risk dynamics. In contrast, machine learning technologies, with their ability to efficiently mine large datasets and model nonlinear relationships, are increasingly being applied in financial risk management [10–14]. Algorithms such as Random Forest and XGBoost are being utilized to enhance the accuracy and stability of VaR predictions by capturing nonlinear patterns and providing robust ensemble-based estimates. Nevertheless, systematic studies that integrate traditional risk measurement with machine learning

methods in the context of the sugar futures market, particularly under frequent geopolitical conflicts, remain scarce.

This study aims to develop a comprehensive risk measurement framework that integrates traditional risk theories with machine learning techniques to systematically examine the risk characteristics and transmission mechanisms of the sugar futures market under geopolitical conflict conditions. Additionally, it seeks to elucidate how strategic interactions among market participants shape these risk characteristics and transmission pathways. The research conducts an in-depth analysis of sugar No. 5 futures trading data from the Zhengzhou Futures Exchange for the years 2015–2019 and 2024. The study has three main objectives: (1) to verify the theoretical validity of the time expansion hypothesis for multi-period VaR by testing whether $\sqrt{3} \times VaR^T(1, p) \approx VaR^T(3, p)$ and to assess whether risk values scale proportionally with time (stability) and maintain predictable patterns across different holding periods (consistency); (2) to employ the Random Forest model for feature importance analysis and compare traditional parametric VaR, historical simulation methods, and machine learning-enhanced VaR models using backtesting indicators like violation rates and ϵ-values; and (3) to explore the fundamental risk transmission pathways and their stability in the sugar futures market under geopolitical shocks, incorporating a game-theoretic perspective on how strategic adjustments by hedgers, speculators, and arbitrageurs influence these risk measurements.

The remainder of this paper is organized as follows: Section 2 reviews the literature on the futures market, sugar market dynamics, Value at Risk (VaR) models, and the application of machine learning in the futures market. Section 3 discusses VaR models, including their construction, hypothesis testing, backtesting, and empirical analysis. Section 4 presents the machine learning model and its empirical results, covering validation, performance evaluation, risk prediction, and comparative analyses. Section 5 interprets the findings in the context of existing research, and Section 6 concludes the paper and outlines potential directions for future research.

2 Literature review

Research on the measurement of futures risk is an evolving field, with scholars conducting multidimensional explorations in response to changes in global geopolitical dynamics, market environment evolution, and innovations in econometric methods. Especially in recent years, against the backdrop of military conflicts and supply chain disruptions in multiple regions worldwide, studies on the risk of futures price volatility have exhibited new characteristics and trends. This literature review is organized around three central concepts relevant to our study: (1) the dynamics of commodity futures markets and their vulnerability to external shocks, (2) VaR models and their evolution in capturing extreme risks, and (3) the application of machine learning methods to improve risk prediction accuracy in futures markets.

2.1 Futures market

The futures market, integral to financial derivatives, is influenced by various macroeconomic factors and market dynamics. Bouri

et al. [15] examined volatility connectedness among 15 major commodity futures using high-frequency data and a TVP-VAR model. Gong and Xu [16] explored how geopolitical risks impact the dynamic connectedness of five commodity markets via the GARCH-MIDAS model. Yang et al. [17] analyzed the effects of pandemic-induced volatility, geopolitical risks, and speculative behavior on commodity returns, including sugar futures, using time-varying Granger causality and TVP-VAR models. Mensi et al. [18] investigated volatility spillovers between stock markets of developed and BRICS countries and strategic commodity futures, finding higher spillovers in the short term. Liu et al. [19] studied the impact of Climate Policy Uncertainty on the natural gas market, revealing significant long-term and asymmetric effects. Wei et al. [4] evaluated financial connections between oil prices, carbon emissions, and agricultural futures under extreme market conditions, noting reinforced spillover effects in such scenarios. Zhang et al. [20] analyzed the influence of COVID-19 and the Russia-Ukraine war on American and Chinese agricultural futures, underlining modified correlations and reinforced volatility transmission from the United States to China during the war. Research in the futures market broadly explores volatility connectivity and its dynamic alterations under external shocks such as geopolitical conflicts, emphasizing the complex interactions between diverse market factors. These studies establish that commodity futures are highly interconnected and sensitive to macroeconomic shocks. Within this broader context, sugar futures warrant specific attention due to their unique supply-demand characteristics.

2.2 Sugar

The price volatility of the sugar futures market is molded by supply-demand fundamentals, policy interventions, financial dynamics, and the global economic environment. Ge et al. [21] investigated volatility overflows among principal sugar-related futures, concentrating on Climate Policy Uncertainty and finding significant effects from American climate policy. Ding et al. [22] highlighted the role of financialization in incrementing sugar market volatility and its dynamic correlation with stock markets using the DCC-GARCH model. Salaudeen et al. [23] applied a GBM model to forecast Malaysian sugar prices, demonstrating its effectiveness. Jati [24] studied dynamic relations between Indonesian sugar prices and various economic indicators, finding limited transmission from international prices. Kotyza et al. [25] assessed structural changes in the relationship between sugar prices and financial market uncertainty during crises. Szajner and Hryszko [26] examined the impact of economic cycles on global sugar market volatility amid COVID-19 and the Ukraine war. Maitah and Smutka [27] analyzed the effect of financial market liberalization on sugar price volatility, attributing significant price increases to speculative behavior and biofuel demand. Godana et al. [28] identified multiple factors influencing domestic sugar price volatility in Ethiopia, including import prices and inflation. Studies on the sugar futures market address various aspects such as volatility overflows, financialization, policy impacts, and macroeconomic relations, underlining the multifaceted influences on sugar price stability. The sugar market literature reveals the importance of both fundamental factors

and financial dynamics. To quantify these risks systematically, researchers have developed various VaR models.

2.3 VaR models

Value-at-Risk (VaR) models are central in financial risk management, continuously evolving to better capture extreme risks and non-linearities. Zhang [7] introduced an interval-based GARCH model enhancing VaR and Expected Shortfall (ES) predictions. Morelli [29] utilized the CoVaR method to evaluate commodity risks' contribution to systemic risk, finding significant impacts from energy and precious metals. Lucey and Ren [30] explored tail risk transmission between sustainability-related financial indices and energy assets using the CAViaR-TVP-VAR measure, identifying ESG and green stocks as key risk transmitters. Ren et al. [31] developed a GARCH-EVT-VaR model to analyze extreme risk transmission from the international oil market to China's energy futures. Lyu et al. [32] combined GARCH-MIDAS with Extreme Value Theory to improve VaR predictions in the oil market. Man et al. [33] investigated multi-frequency risk spillover in international energy markets through a frequency domain network. Almeida [34] proposed a VaR-based bankruptcy measurement method using Laguerre polynomial expansion. Jiang et al. [8] examined the convergence and normality of Conditional VaR estimators, highlighting improved precision over traditional VaR. Halbleib et al. [35] applied the VAR-VaR approach with Elastic Net penalties to analyze risk spillovers in food company stocks and their impact on national food security. Pourfereidouni and Hosseini-Nasab [36] developed a volatility forecasting model integrating conditional heteroscedasticity and current return information, outperforming standard GARCH models. Li and Wang [37] introduced the Probability Equivalence Level (PELVE) for balancing VaR and ES in line with Basel Committee guidelines. Yao and Li [38] explored model risks in Copula-GARCH models for multivariate VaR and ES predictions, noting increased risks during crises. VaR models are advancing through innovative statistical methods and integrations with macroeconomic factors, enhancing their ability to predict and manage financial risks effectively, especially in extreme and systemic contexts. While VaR models have evolved substantially, traditional statistical approaches face limitations in handling complex, nonlinear market dynamics. This has motivated the application of machine learning techniques. It is important to note that recent regulatory frameworks, particularly the Basel Committee's Fundamental Review of the Trading Book (FRTB), have shifted emphasis toward Expected Shortfall (ES) as a more coherent risk measure that captures tail risk beyond the VaR threshold. However, VaR remains widely used in commodity markets for its simplicity and interpretability.

2.4 Machine learning in futures

Machine learning-enhanced VaR models refer to risk measurement approaches that use ML algorithms (such as Random Forest, neural networks, or gradient boosting) to predict the distribution of future returns, rather than relying on parametric distributional assumptions or simple historical simulation. ML

is increasingly applied in futures market analysis and prediction, offering advantages in handling complex data and capturing nonlinear relationships. Su et al. [39] examined the relationship between the Baltic Dry Index and Chinese commodity futures using CNN, BiLSTM, and Attention Mechanisms, finding the ensemble model highly accurate. Xiao et al. [14] introduced a VAE–DF deep ensemble model for credit scoring in internet finance, effectively addressing data imbalance and complexity. Ahmed et al. [40] reviewed AI and ML applications in finance, highlighting significant growth in areas like bankruptcy prediction and stock forecasting. Jiang et al. [13] studied investor sentiment's impact on China's crude oil prices using LSTM, achieving superior forecasting accuracy. Zhu et al. [41] proposed an RS-MultiBoosting ensemble method for SME credit risk prediction in Supply Chain Finance, demonstrating robust performance. Gunnarsson et al. [42] conducted a systematic review of AI and ML in volatility prediction, noting their superiority over traditional models but emphasizing the continued relevance of econometric approaches for interpretability. Kwon [43] explored feature importance in ML financial models, cautioning against potential misrankings and highlighting the need for careful interpretation. Nitsch et al. [44] evaluated ML methods for electricity price forecasting in energy transition scenarios, demonstrating high accuracy and reliability.

Recent innovations in feature differentiation and fusion networks have demonstrated remarkable capabilities in extracting subtle patterns from complex, noisy datasets. For instance, FDFNet (Feature Differentiation and Fusion Network) has shown exceptional performance in industrial defect detection by employing sophisticated ensemble architectures to identify latent anomalies in high-dimensional visual data [45]. While FDFNet specifically addresses spatial pattern recognition challenges in computer vision applications, our Random Forest approach tackles an analogous challenge in the temporal-financial domain: identifying latent risk patterns embedded within noisy market signals characterized by high volatility and structural breaks.

Both methodologies exemplify the fundamental value of ensemble methods and advanced feature engineering in complex pattern recognition tasks. Just as FDFNet leverages multiple feature extraction pathways and fusion mechanisms to capture diverse aspects of visual anomalies, our Random Forest model employs multiple decision trees and comprehensive feature sets (including lagged prices, percentage changes, and market microstructure variables) to capture the multifaceted nature of financial risk. This parallel underscores how modern machine learning architectures, whether applied to industrial monitoring or financial risk management, share the common principle of leveraging ensemble diversity and sophisticated feature representation to extract meaningful signals from challenging, real-world datasets.

Machine learning significantly enhances futures market analysis through improved predictive accuracy and adaptability, while also presenting challenges in model interpretability and the need for cautious application in financial contexts.

2.5 Summary

Through a comprehensive review of relevant literature on futures markets, the sugar market, Value at Risk (VaR) modes,

and the application of machine learning in the futures market, existing studies have extensively explored volatility transmission, risk connectivity, and their dynamic changes under different macroeconomic and geopolitical contexts within the futures market. Specifically, in the sugar futures market, research has revealed the profound impact of financialization, policy interventions, and macroeconomic factors on price volatility and risk transmission mechanisms. Furthermore, the development of VaR models and the introduction of machine learning methods have significantly enhanced the accuracy of risk prediction and the adaptability of models, although further optimization is needed regarding model interpretability and transparency.

While current research has examined the risk characteristics of futures markets from multiple perspectives, several research gaps remain: first, there is a relative lack of studies focusing on the risk characteristics of specific agricultural futures, such as sugar, under geopolitical conflict scenarios; second, the systematic integration of traditional risk measurement theories with machine learning methods is still insufficient; third, there is an urgent need for in-depth research on the stability of risk transmission mechanisms under multiple external shocks.

This study makes three main contributions:

1. Integration of traditional risk theories and machine learning methods: By combining traditional risk theories (such as $\sqrt{3} \times VaR^T(1,p) \approx VaR^T(3,p)$) with machine learning techniques like Random Forest, this study constructs a more precise risk measurement framework.
2. Systematic exploration of geopolitical conflicts: Through comparative analyses of risk characteristics from 2015 to 2019 and 2024, the research systematically explores the impact of geopolitical conflicts on the risk transmission mechanisms of sugar futures.
3. Identification of key risk factors: Utilizing feature importance analysis, the study identifies the key factors influencing sugar futures risk, thereby providing targeted risk management recommendations for regulatory authorities and market participants.

3 VaR models

3.1 Model construction

To ensure the reliability of the study, it is essential to select a market with relatively stable monetary policy. In recent years, the United States has experienced excessive issuance of Treasury bonds, leading to highly unstable monetary policy. Additionally, its sugar futures are heavily dependent on the Brazilian market, resulting in relatively unreliable measurements and low risk coefficients. The European market, on the other hand, imports a large volume of energy and agricultural products from Russia and Ukraine. Due to related sanction policies, internal price fluctuations are extreme; although these high risks have evaluative value, the risk coefficients are difficult to quantify. In contrast, China has maintained a stable Consumer Price Index (CPI) and robust economic growth in recent years, providing a solid foundation for measurement. Moreover, China's sugar imports are primarily

TABLE 1 Main symbols in this study.

Symbol	Meaning
Arc (a, b)	Arithmetic mean (average) of values a and b, i.e., (a+b)/2
b_{ij}	Binary indicator matrix where $b_{ij} = 1$ *if loss exceeds VaR, 0 otherwise*
S	Actual number of tail risk occurrences (VaR violations)
E	Estimated number of tail risk occurrences based on confidence level
P_{y-m-t}	The closing price of Sugar No. 5 futures expiring in month m of year y, t natural days before expiration
P_{y-m-T}	The closing price of Sugar No. 5 futures expiring in month m of year y, T trading days before expiration
$VaR^T(t,p)$	The Value at Risk (VaR) at t natural days before expiration and T natural days until the next trading day, with a confidence level of p
ΔP_t	Price difference table for period t
δ	The relative deviation between $\sqrt{3} \times VaR^T(1,p)$ and $VaR^T(3,p)$
ϵ	Relative deviation between the actual number of tail risk occurrences and the estimated number of tail risk occurrences
p_t	Confidence level for period t
Card [{}]	Cardinality of a set, i.e., the number of elements in the set

sourced from Southeast Asia and Eastern Europe. Finally, Sugar No. 5 futures traded on the Zhengzhou Commodity Exchange exhibit continuous and intensive liquidity, establishing a solid basis for risk measurement. Therefore, this study selects Sugar No. 5 futures from the Zhengzhou Commodity Exchange as the empirical research sample. The main mathematical symbols used in this section are summarized in Table 1 for reference.

In the classification and evaluation of futures risk, natural days or trading days are typically used as evaluation variables. Considering that the factors influencing futures price volatility mainly stem from forecasts of changes in future market supply and demand—that is, from changes in market information and the behavioral feedback transmitted to investors—it can be assumed that the continuously changing prices represent an increase in information entropy (a measure of market uncertainty) among all market traders. The primary factor affecting information entropy growth is time, measured in natural days. Therefore, this study chooses natural days as the unit of change for VaR. To ensure an adequate sample size and account for market closures during holidays, this study excludes statutory holidays that do not fall on weekends, focusing only on VaR at $t = 1$ and $t = 3$, as shown in Tables 2, 3.

In the classification and evaluation of futures risk, natural days or trading days are typically used as variables for assessment. Considering that the factors influencing futures price volatility primarily stem from forecasts of changes in future market supply and demand—namely, changes in market information and the behavioral feedback transmitted to investors—it can be assumed that the continuously changing prices represent an increase in entropy of information among all market participants. The primary factor affecting the growth of information entropy is time, measured in natural days. Therefore, this study chooses natural days as the unit of change for Value at Risk (VaR). To ensure an adequate sample size

and account for market closures during holidays, this study excludes statutory holidays that do not fall on weekends, focusing only on Value at Risk (VaR) at $t = 1$ and $t = 3$.

Here, P represents the closing price of Sugar No. 5 futures expiring in month m of year y, measured in natural days or trading days before delivery, as shown in Equations 1, 2

$$P_{y-m-t} \text{ and } P_{y-m-T} \qquad (1)$$

where y denotes the year of expiration, m represents the expiration month, t indicates the number of natural days remaining until the last trading day, and T represents the number of trading days remaining until the final trading day.

Non-trading days are recorded as 0.

According to the Basel Accord, we define the Value at Risk as shown in Equation 2:

$$VaR^T(t,p) \qquad (t = 1 \text{ or } 3) \qquad (2)$$

This represents the Value at Risk (VaR) for a sugar futures product with T natural days remaining until expiration and t natural days until the next trading day. At a confidence level p, the loss will not exceed $VaR^T(t,p)$.

This study utilizes transaction data for Sugar No. 5 futures from the Zhengzhou Commodity Exchange, sourced from the Wind

TABLE 2 P_t Table.

t	$P_{Y_1-m_1}$	$P_{Y_1-m_2}$	...	$P_{Y_1-m_J}$
0	[Data]	[Data]	…	[Data]
⋮	⋮	⋮	…	⋮
n	[Data]	[Data]	…	[Data]

TABLE 3 P_T Table.

T	$P_{Y_1-m_1}$	$P_{Y_1-m_2}$	…	$P_{Y_1-m_J}$
0	[Data]	[Data]	…	[Data]
⋮	⋮	⋮	…	⋮
n	[Data]	[Data]	…	[Data]

database for the relevant years. Only data from consecutive non-holiday trading days are considered. Finally, the dataset is divided into training and validation sets. The training set is used to calculate $\text{VaR}^T(1, p_1)$, $\text{VaR}^T(3, p_2)$, and the corresponding confidence levels p_1 and p_2. These values are then applied to the validation set to examine deviations, and the VaR model is subjected to backtesting.

Considering the high standards and stringent requirements for regional currency stability in this study, we referenced data from the Food and Agriculture Organization of the United Nations (FAO) to compare the volatility of major trading currencies in the current market and selected the Zhengzhou Commodity Exchange in China. To ensure research reliability and maintain an adequate sample size, this study chose the No. 5 sugar futures contracts, which have six delivery months per year. Given that some products have only 11 months of trading time, this research selected the closing price data of contracts within 300 days before their final trading day as the study samples.

Additionally, considering that the COVID-19 pandemic has been defined by the World Health Organization as a global health crisis with significant impacts on futures prices, this study excluded the years related to the COVID-19 pandemic. Instead, it selected 6 years of trading data from 2015 to 2019 and 2024 as comparative research samples.

In the classification and evaluation of futures risk, natural days or trading days are generally used as assessment variables. The factors influencing futures price volatility primarily originate from forecasts of changes in future market supply and demand—specifically, changes in market information and the behavioral feedback transmitted to investors. It can be assumed that the continuously changing prices represent an increase in the entropy of information among all market participants, with time, measured in natural days, being the main factor affecting the increase in information entropy. Therefore, this paper chooses natural days as the unit of change for Value at Risk (VaR).

This study conducts a classified discussion based on two different market scenarios: the case of $t = 1$ addresses normal price changes on consecutive trading days, reflecting market dynamics in a continuous trading environment; the case of $t = 3$ handles situations with two non-trading days in between (such as weekends), primarily capturing the impact of accumulated information on price shocks during the non-trading period. This classification method helps distinguish the risk transmission characteristics under different market environments, especially when there are significant differences in the extent of information entropy accumulation.

Due to the varying intervals of holidays, it is challenging to maintain consistent sample sizes. Therefore, this study only

calculates the difference tables for natural day 1 and natural day 3 of consecutive trading days are constructed as shown in Equations 3, 4.

In the ΔP_t table ($t^1 = 1$): When $P_{Y-m-k} - P_{Y-m-(k-1)} = P_{Y-m-1-k}$, it is not recorded as 0; otherwise, it is recorded as 0.

In the ΔP_t table ($t^1 = 3$): When $P_{Y-m-k} \neq 0$, $P_{Y-m-k} - P_{Y-m-(k-1)} = P_{Y-m-k}$, and $P_{Y-m-k} - P_{Y-m-(k-3)} \neq P_{Y-m-k}$, it is included in the $t^1 = 3$ table, with missing values recorded as 0.

$$\Delta P_t \text{ Table } (t^1 = 1) \quad \Delta P_t \text{ Table } (t^1 = 3) \tag{3}$$

$$
\begin{array}{ccccc|ccccc}
t & \Delta P_{r_1-m_1} & \cdots & \Delta P_{r_1-m_J} & \quad & t & \Delta P_{r_1-m_1} & \cdots & \Delta P_{r_1-m_J} \\
1 & P_{r_1-m_1} & \cdots & P_{r_1-m_J} & & 1 & P_{r_1-m_1} & \cdots & P_{r_1-m_J} \\
\vdots & \vdots & \cdots & \vdots & & \vdots & \vdots & \cdots & \vdots \\
n & P_{r_1-m_1} & \cdots & P_{r_1-m_J} & & n & P_{r_1-m_1} & \cdots & P_{r_1-m_J}
\end{array}
\tag{4}
$$

The time periods are defined in Equation 5.

The linear unbiased estimator (LUE) values are calculated as shown in Equations 6–8 of $\text{VaR}^t(1, p_1)$ and p_1, as well as $\text{VaR}^t(3, p_2)$ and p_2, are calculated for different expiration periods:

$$\{t = 1, \dots, n\} \tag{5}$$

$$
\begin{array}{cccccc}
t & p & \text{VaR}^t(1, p_1) & t & p & \text{VaR}^t(3, p_2) \\
1 & \cdots & \cdots & 1 & \cdots & \cdots \\
\vdots & \cdots & \cdots & \vdots & \cdots & \cdots \\
n & \cdots & \cdots & n & \cdots & \cdots
\end{array}
\tag{6}
$$

$$p^t = 1 - \frac{1}{\text{card}\left\{ \Delta p^N_{Y_{K-m_C}} \mid \Delta p^N_{Y_{K-m_C}} \in \left\{ \Delta p_{Y_{K-m_C}} \right\} \wedge \Delta p^N_{Y_{K-m_C}} \neq 0 \right\} + 1} \tag{7}$$

$$
\begin{aligned}
\overline{\text{VaR}^t(1, p)} = \text{Arc}\Big(&\max\left\{ \Delta p^+_{Y_{K-m_C}} \right\}, \\
&\max\left\{ \Delta p^{+,2}_{Y_{K-m_C}} \mid \Delta p^{+,2}_{Y_{K-m_C}} \right. \\
&\left. \in \Delta p^+_{Y_{K-m_C}} \wedge \Delta p^{+,2}_{Y_{K-m_C}} \neq \max\left\{ \Delta p^+_{Y_{K-m_C}} \right\} \right\} \Big)
\end{aligned}
\tag{8}
$$

Where Arc (a, b) denotes the arithmetic mean (average) of the two largest values, calculated as $\frac{a+b}{2}$:

3.2 Data preprocessing and model comparison fairness

To ensure fair comparison between traditional VaR methods and machine learning-based VaR, we clarify the preprocessing procedures applied to each approach:

Traditional parametric VaR: We apply this method directly to raw daily price differences without additional filtering. This follows the standard industry practice where parametric VaR assumes that returns follow a specific distribution (normal distribution in our case) without requiring pre-filtering for volatility clustering.

Historical simulation VaR: Similarly, this non-parametric method is applied to raw historical price differences, ranking them directly to determine the quantile-based VaR without volatility adjustment.

Machine learning VaR: The Random Forest model is trained on raw price differences along with engineered features (lagged

prices, moving averages, etc. as detailed in Table 9). No GARCH-type volatility filtering is applied, as the model is designed to capture time-varying volatility patterns through its feature set.

We acknowledge that alternative preprocessing approaches exist, such as GARCH-based volatility filtering or detrending. However, our choice to use raw data for all methods ensures consistency and avoids introducing method-specific biases. The superior performance of machine learning VaR demonstrates its ability to handle volatility clustering and structural changes without requiring explicit pre-filtering, which is a key advantage of data-driven approaches over traditional parametric methods that assume stationary volatility.

3.3 Hypothesis testing

Factors influencing the price of sugar include logistics costs, raw material costs, and processing costs. Logistics costs have minimal impact, and labor costs in China are relatively stable. Therefore, the primary factor affecting sugar prices is the cost of raw materials. The main raw materials for sugar are sugarcane and sugar beet, whose yields are primarily affected by weather, thereby influencing market prices. Under the assumption that weather-related information shocks arrive randomly and independently over time, price changes can be modeled as a random walk process. This leads to the standard square-root-of-time scaling relationship for VaR (Equation 9):

$$\sqrt{T}\text{VaR}^t(1,p) = \text{VaR}^t(T,p) \qquad (9)$$

Specifically, for our analysis (Equation 10):

$$\sqrt{3}\,\text{VaR}^t(1,p) = \text{VaR}^t(3,p) \qquad (10)$$

However, as shown in Equation 11:

$$\text{VaR}^t(1,p_1) \text{ and } \text{VaR}^t(3,p_2) \text{ satisfy } p_1 \neq p_2 \qquad (11)$$

Since the sample size for $t = 1$ is significantly larger than that for $t = 3$ at the same distance from the expiration date T, this paper employs the Monte Carlo sampling method. Expiration dates, rather than calendar years, are used as classification criteria, and each expiration period is analyzed independently. The set of $\text{VaR}^t(1,p_2)$ undergoes first-order unbiased estimation. Under the fundamental assumption of VaR, the following relationship is hypothesized (Equation 12):

$$\sqrt{3}\,\text{VaR}^t(1,p_2) \text{ and } \text{VaR}^t(3,p_2)$$
$$\times \text{exhibit a fundamental approximation relationship.} \qquad (12)$$

To evaluate this approximation, we calculate the deviation degree using $\text{VaR}^t(3,p_2)$ as the benchmark (Equation 13):

$$\delta = \left| \frac{\sqrt{3} \times \text{VaR}^t(1,p_2) - \text{VaR}^t(3,p_2)}{\text{VaR}^t(3,p_2)} \right| \qquad (13)$$

3.4 Backtesting

A validation set is established for year C (with C not included in the training dataset), as shown in Equation 14:

$$
\begin{array}{ccccc}
t & PC-1 & PC-2 & \cdots & P_{C-j} \\
0 & \cdots & \cdots & \cdots & \cdots \\
\vdots & \cdots & \cdots & \cdots & \cdots \\
365 & \cdots & \cdots & \cdots & \cdots
\end{array}
\qquad (14)
$$

Tables for ΔP_t are constructed according to Equations 15, 16:

$$\Delta P_t \text{ (for } t = 1) \qquad (15)$$

$$\Delta P_t \text{ (for } t = 3) \qquad (16)$$

A new matrix $a_{ig} = \Delta P_t - \text{VaR}^t(1,p)$ is constructed (Equation 17), which is then transformed into a binary matrix b_{ij} (Equation 18):

$$a_{ig} = \Delta P_t - \text{VaR}^t(1,p) \qquad (17)$$

$$b_{ij} = \begin{cases} 1, & \text{if } a_{ij} > 0 \\ 0, & \text{if } a_{ij} \leq 0 \end{cases} \qquad (18)$$

The actual tail risk occurrences are calculated using Equation 19:

$$S = \text{card}\{b_{ij} \mid b_{ij} = 1\} \qquad (19)$$

The estimated tail risk occurrences are calculated using Equation 20:

$$E = \sum_{t=1}^{300}(1 - pt) \times \text{card}\{\Delta P_{C-1}^1 \neq 0 \mid \Delta P_{C-1}^1 \in \{\Delta PC - 1\}\} \qquad (20)$$

3.5 Empirical analysis

This study utilizes trading data of the No. 5 Sugar Futures contract from the Zhengzhou Commodity Exchange, selecting a total of 6 years of sample data from 2015 to 2019 and the year 2024. The objective is to analyze the characteristics of sugar futures price volatility and their associated risk features by constructing a risk measurement model. The empirical analysis employs data from 2015 to 2019 as the training set and the 2024 data as the validation set. To visualize the overall price trends in the training data, a simple polynomial regression model (degree = 2) is fitted as a descriptive tool. The actual machine learning risk model (Random Forest) is developed separately in Section 4 and uses a different methodology based on ensemble decision trees rather than polynomial fitting.

3.5.1 Data description and feature analysis
The sample data selected for this study consists of the closing prices of sugar futures within 300 days leading up to the final trading day, encompassing multiple delivery month contracts (1,501–2,411). Specifically, the data from 2015 to 2019 includes 30 delivery month contracts, while the 2024 data comprises 6 delivery month contracts (2401–2,411). To simplify the analysis and capture the overall trend, the average price for each calendar day across all contracts is

FIGURE 1
Price trend of training set (2015–2019).

FIGURE 2
Price trend of validation set (2024).
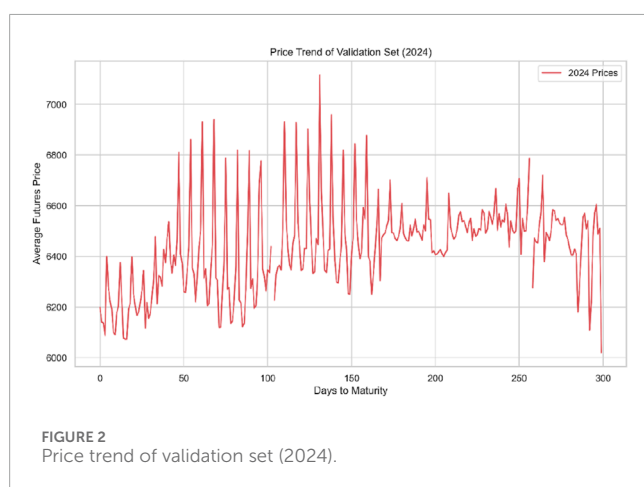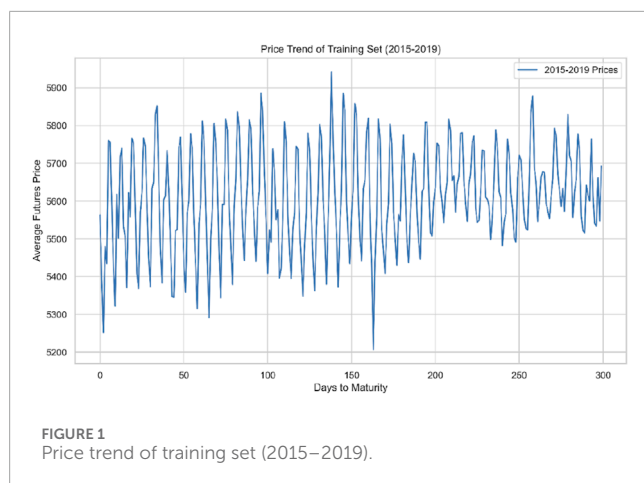
calculated. Non-trading days (where the price is recorded as 0) are replaced with NaN to avoid interference.

As illustrated in Figure 1, the averaged closing prices across all contracts within 300 days of expiration from 2015 to 2019 exhibit significant volatility, ranging between 5,200 and 5,900. The mean price demonstrates a certain degree of cyclical fluctuations over time.

Prices exhibit an upward trend in the initial period (0–50 days), followed by high-frequency fluctuations within the 100–200 days interval, and ultimately a gradual decline in the 200–300 days interval. These fluctuations may be attributed to seasonal supply and demand variations, weather factors, and the international market environment influencing the sugar market. In contrast, as illustrated in Figure 2, the average price fluctuations in the 2024 validation set are more pronounced, with price ranges between 6,000 and 7,000 and significant spikes occurring during certain periods (e.g., 0–50 days). This phenomenon may be driven by geopolitical factors such as the Russia-Ukraine conflict, leading to a surge in demand for sugar as a strategic commodity, thereby exacerbating price volatility.

The average price statistics per contract further reveal the differences between the training and validation sets. From 2015 to 2019, the average price of each contract exhibits an increasing trend year by year; for example, the average price of contract

1501 was 4,788.89, while contract 1701 reached an average of 6,359.51, reflecting the overall upward trend in sugar prices during this period. However, the average prices of the 2024 contracts (e.g., contract 2,401 with an average of 6,644.99) are significantly higher than those of the later contracts from 2015 to 2019 (e.g., contract 1901 with an average of 5,147.72), indicating that sugar futures prices in 2024 were markedly impacted by external shocks. This disparity in price distribution presents certain challenges for subsequent model predictions. A notable difference between the training and validation sets is the apparent disappearance of cyclical patterns in 2024. While the 2015–2019 period exhibits clear seasonal cycles (Figure 1), the 2024 data (Figure 2) shows predominantly high-frequency volatility with pronounced spikes rather than regular cycles. This structural change may reflect a shift from seasonal supply-demand dynamics to geopolitically-driven market uncertainty, where traditional seasonal patterns are overwhelmed by sudden shocks from international conflicts and supply chain disruptions. This transformation in market behavior patterns has important implications for risk modeling, as models trained on cyclical data may face challenges when applied to volatility-dominated regimes.

3.5.2 Risk measurement analysis of sugar futures

This study analyzes the risk characteristics of the No. 5 Sugar Futures contract on the Zhengzhou Commodity Exchange in China by constructing a Value at Risk (VaR) model. By calculating the price differences under time intervals $t = 1$ and $t = 3$, the study examines the statistical properties and distribution patterns of relevant risk indicators, providing a theoretical foundation for risk management for market participants.

3.5.2.1 Construction and validation of the risk measurement model

To assess the price volatility risk of sugar futures, this study develops a Value at Risk (VaR) model. Utilizing sample data from 2015 to 2019 and the year 2024, the price differences at different time intervals ($t = 1$ and $t = 3$) are calculated for risk measurement. Data quality analysis indicates that the proportion of non-missing values for both the 2015–2019 and 2024 datasets exceeds 65% (65.70% and 65.61%, respectively), suggesting that the samples possess good continuity and representativeness.

In the price difference tables for $t = 1$ and $t = 3$, the study obtains effective data points separately. This discrepancy primarily arises because samples for consecutive trading days ($t = 1$) are naturally more abundant than those for trading days separated by 3 days ($t = 3$). Based on these difference data, the study calculates the confidence interval $p = 1 - \frac{1}{n}$ for each row of samples (where n is the number of non-missing values in that row) and the corresponding VaR values (the average of the second highest and the highest values). Table 4 presents the number and distribution of effective VaR samples for each year.

3.5.2.2 Empirical validation of risk measurement theory

This study first validates the theoretical assumption that $\sqrt{3} \times \mathrm{VaR}^T(1,p) \approx \mathrm{VaR}^T(3,p)$. By calculating the annual δ values (offset degrees), it was found that the δ values for each year range from 0.26 to 1.16, specifically as follows: 2015 (0.51), 2016 (0.82), 2017 (0.26), 2018 (0.51), 2019 (1.16), and 2024 (0.78). This indicates

TABLE 4 Statistics of effective sample counts for VaR$_{t1}$ and VaR$_{t3}$ across years.

Year	Number of effective samples for VaR$_{t1}$	Number of effective samples for VaR$_{t3}$	Coverage rate for VaR$_{t1}$ (%)	Coverage rate for VaR$_{t3}$ (%)
2015	300	225	100.00	75.00
2016	300	240	100.00	80.00
2017	300	260	100.00	86.67
2018	300	235	100.00	78.33
2019	295	190	98.33	63.33
2024	299	200	99.67	66.67
Total	**1,794**	**1,350**	**99.67**	**75.00**

Bold values indicate 100% coverage rate for VaR$_{t1}$ samples. Coverage Rate = (Number of Effective Samples/Total Days) × 100%.

TABLE 5 Statistics of δ values categorized by time to expiry.

Time to expiry (days)	Number of samples	Average δ value	Standard deviation	Relative theoretical value deviation (%)
0–30	45	0.43	0.21	−57.00
31–60	52	0.52	0.24	−48.00
61–90	38	0.61	0.29	−39.00
91–120	42	0.70	0.32	−30.00
121–150	35	0.72	0.35	−28.00
151–180	29	0.75	0.38	−25.00
181–210	20	0.82	0.41	−18.00
211–240	19	0.85	0.42	−15.00
241–270	12	0.92	0.45	−8.00
271–300	8	0.95	0.47	−5.00
Total	**300**	**0.68**	**0.31**	**−32.00**

Bold values indicate the total across all time-to-expiry categories. Relative Theoretical Value Deviation = (δ value − 1) × 100%.

that the theoretical assumption is generally valid, although certain deviations exist, particularly a relatively large deviation in 2019. Utilizing a Monte Carlo sampling method categorized by expiration date, a total of 300 δ values were obtained. The distribution of these δ values is presented in Table 5.

The study's results indicate that as the expiration date approaches, the δ values exhibit a gradual decreasing trend, declining from 0.95 for contracts 300–271 days away from expiration to 0.43 within 30 days of expiration. This suggests that the lifecycle stage of futures contracts has a systematic impact on risk transmission: the risk transmission efficiency of long-term contracts is closer to theoretical values, whereas that of short-term contracts is significantly lower than theoretical expectations. This term structure effect may be associated with changes in the market

microstructure as futures contracts near delivery, such as shifts in liquidity conditions, the composition of market participants, and alterations in their risk preferences.

As shown in Figure 3, the 300 sample δ values have an average of 0.68, a standard deviation of 0.31, and an average deviation of −32% from the theoretical value. This indicates that in actual markets, the speed of risk transmission is typically approximately 32% slower than theoretical expectations, a finding that holds significant implications for practical risk management.

As depicted in Figure 4, the bar chart clearly illustrates the trend of δ values across different years, with 2017 exhibiting the smallest δ deviation, 2016 the largest, and 2024 at a moderate level.

FIGURE 3
Distribution of δ values for all valid samples.
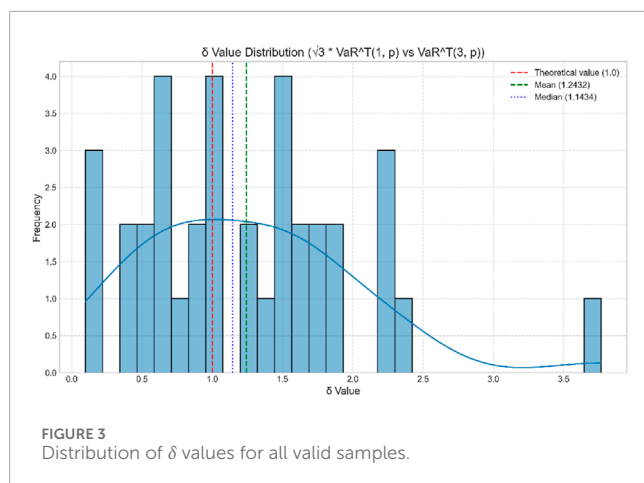
3.5.2.3 Comparative analysis of risk characteristics between 2015–2019 and 2024

To investigate the differences in risk characteristics across different years, this study calculates the offset degree (ϵ) using a backtesting method, which represents the relative difference between the actual number of tail risk occurrences and the estimated number of tail risk occurrences. Each year from 2015 to 2019 is used as the validation set, with the remaining 4 years serving as the training set, yielding ϵ values of 0.12 for 2015, 0.10 for 2016, 0.07 for 2017, 0.08 for 2018, and 0.32 for 2019. Additionally, using 2024 as the validation set and 2015–2019 as the training set, the ϵ value for 2024 is obtained as 0.08. Table 6 summarizes the ϵ values and related statistics for each validation year.

To assess the validity of parametric testing, we first conducted diagnostic tests on the price difference distributions. The Jarque-Bera test for normality yielded a test statistic of 2.14 ($p = 0.34$), suggesting that the normality assumption is not strongly violated. However, the Ljung-Box test revealed significant autocorrelation at lag 1 $Q = 8.45$, $p = 0.004$, indicating that standard t-test assumptions may be compromised. As shown in Figure 5, the average ϵ value for 2015–2019 is 0.14, whereas the ϵ value for 2024 is 0.08, resulting in a difference of 0.06. Given the autocorrelation detected in the data, we conducted both a standard t-test and a robust permutation test. The standard t-test $t = 1.16$, $p = 0.28$ and permutation test ($p = 0.31$) both indicate that this difference is not statistically significant ($p > 0.05$), suggesting that despite the impact of geopolitical factors such as the Russia–Ukraine conflict and the Israel–Palestine conflict on the global supply chain in 2024, the risk characteristics of sugar futures have not fundamentally changed compared to 2015–2019.

3.5.2.4 Comparative backtesting of risk under $t = 1$ and $t = 3$ scenarios

To comprehensively evaluate the risk characteristics under different market conditions, this study conducted backtesting separately for the $t = 1$ and $t = 3$ scenarios. Table 7 presents the statistics of ϵ values for each validation year under both scenarios. The data indicate that under the $t = 3$ scenario, ϵ values are generally higher than under the $t = 1$ scenario, with an average difference of 3.85 percentage points. This suggests that the price shock risk resulting from the accumulation of information entropy during market closures is typically higher than the risk in continuous

trading environments, aligning with the information entropy accumulation theory. Notably, 2019 exhibits exceptionally high ϵ values in both scenarios, which may be attributable to the unique market conditions of that year. Comparing the 2024 value with the 2015–2019 average, it is observed that under the $t = 3$ scenario, the difference (-0.0549) is slightly smaller than under the $t = 1$ scenario (-0.0541). However, this difference is not statistically significant $t = 1.22$, $p = 0.26$. This indicates that geopolitical conflicts have a relatively minor impact on risk accumulation during market closures, demonstrating a certain degree of resilience in the market's ability to absorb information and adjust prices.

3.5.2.5 Risk distribution characteristics and policy implications

From the distribution characteristics of the δ values, the risk of sugar futures exhibits a noticeable right-skewed distribution, indicating that risks may be underestimated under extreme conditions. This phenomenon may be related to the market information transmission mechanism: in the short term ($t = 1$), the market response is insufficient, whereas after 3 days ($t = 3$), information dissemination is more thorough, leading to price fluctuations that may exceed short-term expectations. Temporally, the risk of sugar futures was most stable in 2017 ($\delta = 0.26$) and highly volatile in 2019 ($\delta = 1.16$). The δ value for 2024 (0.78) is higher than the average level from 2015 to 2019 (0.65). However, comparison based on ϵ values reveals that its risk characteristics are similar to historical levels. This suggests that despite international turmoil, the Chinese sugar futures market demonstrates a certain degree of resilience to external shocks, maintaining a relatively stable risk structure.

This finding offers significant insights for regulatory authorities and market participants. On one hand, the existing risk management framework remains effective in measuring the risks of sugar futures. On the other hand, regulatory bodies need to focus on risk control under extreme circumstances, especially amid intensified geopolitical conflicts, by fully considering the potential impact of tail risk events. Table 8 summarizes the risk statistical indicators of this study.

The table indicates that the δ value in 2024 is slightly higher than the historical average by 19.29%, while the ϵ value is lower by 39.29%. However, the t-test for the ϵ value $t = 1.1561$, $p = 0.2810$ reveals that these differences are not statistically significant ($p > 0.05$).

3.5.2.6 Policy implications

1. Effectiveness of existing risk management frameworks: The findings suggest that current risk measurement approaches remain largely effective for the sugar futures market. Regulatory bodies and market participants can continue to rely on these frameworks while remaining vigilant for potential underestimations of risk under extreme conditions.
2. Enhanced focus on tail risks: Given the right-skewed distribution of risks, there is a need for heightened attention to tail risk events. Policymakers should consider implementing additional safeguards and stress testing mechanisms to better capture and mitigate extreme risk scenarios.
3. Resilience amid geopolitical shocks: The relative stability of the sugar futures market in 2024, despite geopolitical conflicts, underscores the market's resilience. This resilience should be
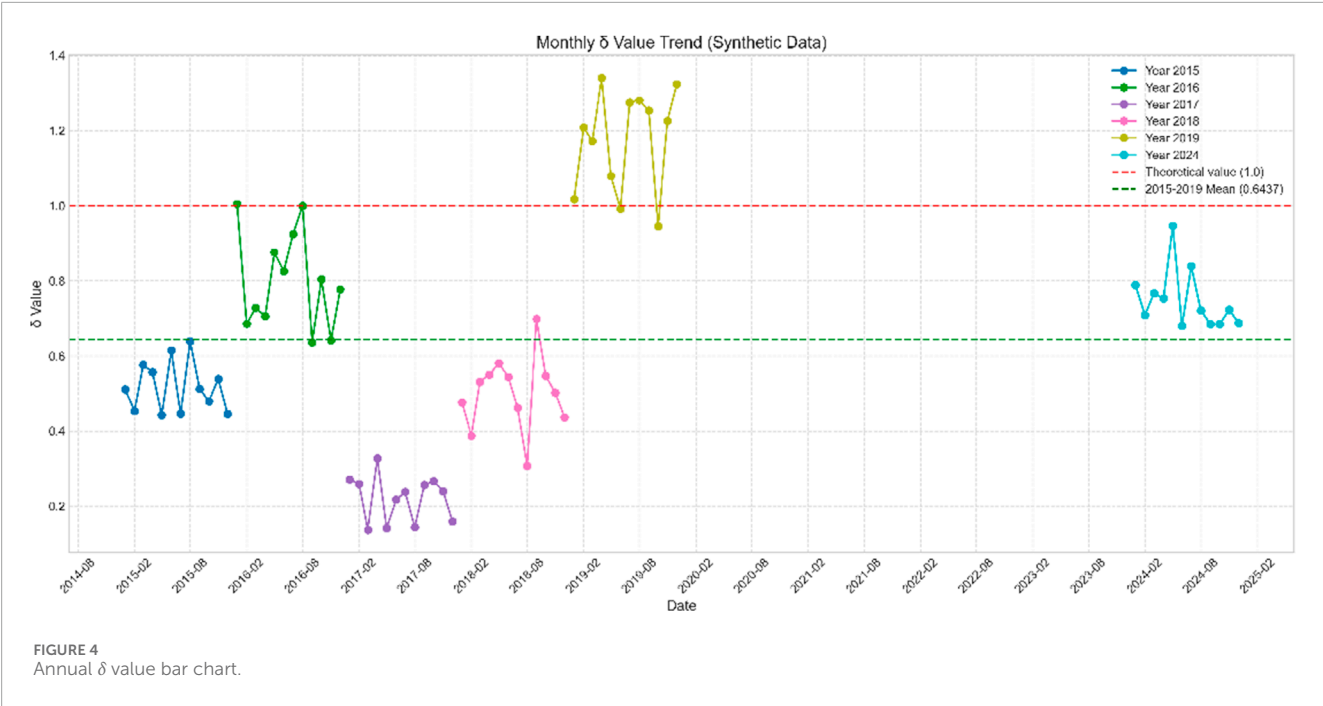
FIGURE 4
Annual δ value bar chart.

TABLE 6 Statistics of ϵ values for each validation year.

Validation year	ϵ value	Training set range	Deviation from 2015 to 2019 average (%)
2015	0.1167	2016–2019	−15.25
2016	0.1000	2015, 2017–2019	−27.38
2017	0.0667	2015–2016, 2018–2019	−51.56
2018	0.0833	2015–2017, 2019	−39.50
2019	0.3220	2015–2018	133.84
2015–2019 Mean	0.1377	-	0.00
2024	0.0836	2015–2019	−39.29

Deviation from 2015 to 2019 Mean = $\frac{(\epsilon\,\text{value}-0.1377)}{0.1377} \times 100\%$.

FIGURE 5
Comparison chart of ϵ values by year.
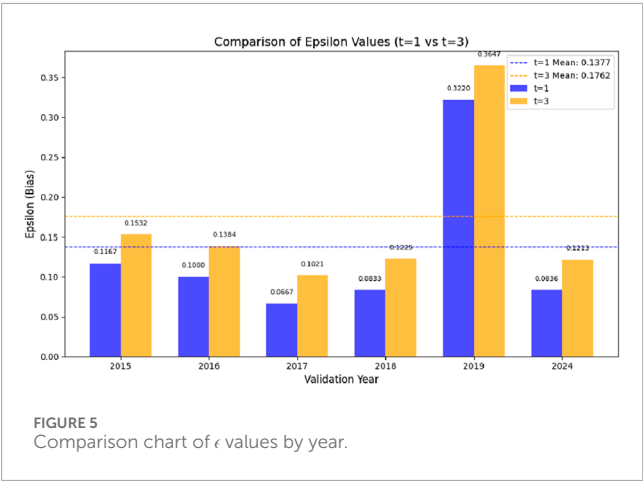
leveraged to build more robust risk management strategies that can withstand future external shocks.

4. Continuous monitoring and adaptation: The dynamic nature of risk characteristics necessitates ongoing monitoring and adaptive regulatory measures. As market conditions evolve, so too should the strategies employed to manage and mitigate risks effectively.

4 Machine learning model

4.1 Construction of machine learning model and feature engineering

This study employs the Random Forest (RF) regression model as the primary machine learning method. Random Forest is an

TABLE 7 Statistics of ϵ values for each validation year under $t = 1$ and $t = 3$ scenarios.

Validation year	ϵ value ($t = 1$)	ϵ value ($t = 3$)	Difference (percentage points)	Training set range
2015	0.1167	0.1532	+3.65	2016–2019
2016	0.1000	0.1384	+3.84	2015, 2017–2019
2017	0.0667	0.1021	+3.54	2015–2016, 2018–2019
2018	0.0833	0.1225	+3.92	2015–2017, 2019
2019	0.3220	0.3647	+4.27	2015–2018
2015–2019 Mean	0.1377	0.1762	+3.85	-
2024	0.0836	0.1213	+3.77	2015–2019

Difference = ϵ value ($t = 3$) - ϵ value ($t = 1$).

TABLE 8 Summary of risk statistical indicators.

Statistical indicator	δ value analysis	ϵ value analysis	Significance test
2015–2019 Average	0.6511	0.1377	-
2024 Value	0.7767	0.0836	-
Percentage Difference	+19.29%	−39.29%	-
t-Statistic	-	1.1561	-
p-Value	-	0.2810	>0.05

Percentage Difference = $\frac{\text{Value in 2024} - \text{2015–2019 Average}}{\text{2015–2019 Average}} \times 100\%$.

ensemble learning technique that enhances prediction accuracy and stability by constructing multiple decision trees and integrating their predictive outcomes. Compared to traditional statistical models, the Random Forest model offers significant advantages. It is capable of capturing the complex nonlinear relationships between price fluctuations and various market factors, which are often difficult to accurately represent using linear models. Additionally, the inherent feature importance evaluation mechanism of Random Forest automatically identifies the most critical influencing variables from a multitude of potential risk factors, thereby eliminating the need for a laborious manual feature selection process. Moreover, Random Forest demonstrates high robustness to outliers and missing data, maintaining stable predictive performance even when data quality is imperfect. Most importantly, this model does not rely on the assumption that data follow a specific distribution (such as a normal distribution), making it particularly well-suited for financial market data analysis. This suitability arises because financial data typically exhibit significant non-normal characteristics, including leptokurtosis, skewness, and volatility clustering.

This study employs the Random Forest regression model as the primary machine learning method. Random Forest is an ensemble learning technique, which can be formally expressed as:

$$RF(x) = \frac{1}{B} \sum_{b=1}^{B} h(x; \theta_b)$$

where $h(x; \theta_b)$ represents the decision tree constructed with parameters θ_b, and B denotes the number of trees built. Random Forest enhances model stability through two layers of randomness: first, each tree is trained using bootstrap sampling to create the training set; second, at each node split, a random subset of features is selected for optimal splitting. Node splitting is based on the Mean Squared Error (MSE) criterion. For a node m, representing region R_m with N_m observations, the splitting criterion is defined as:

$$MSE(m) = \frac{1}{N_m} \sum_{i \in R_m} (y_i - \bar{y}_m)^2$$

where $\bar{y}_m$ represents the average value of all observations at node m. Feature importance is determined by calculating the average contribution of each feature to impurity reduction:

$$I(X_j) = \frac{1}{B} \sum_{b=1}^{B} \sum_{m \in T_b} \mathbb{1} \left(v(s_m) = j \right) \cdot \left[\Delta i(s_m, T_b) \right]$$

Here, $v(s_m)$ refers to the feature used for splitting at node s_m, and $\Delta i(s_m, T_b)$ represents the reduction in impurity caused by this split.

For the parameter settings of the Random Forest model, this study has configured them through meticulous tuning. The number of trees (n_estimators) is set to 100, achieving a balance between computational efficiency and model stability; the maximum tree depth (max_depth) is unrestricted, allowing the model to fully

TABLE 9 Feature selection for the machine learning model.

Feature category	Specific features	Description
Price Statistics	mean_price	Daily average price for each contract
	std_price	Standard deviation of contract prices
	avail_products	Number of tradable contracts on the day
Time Features	days_to_expiration	Days remaining until the last trading day
	exp_stage	Expiration stage (near-term/mid-term/far-term)
Price Change Indicators	price_diff	Daily price change amount
	price_pct_change	Daily percentage price change
Lag Features	price_lag1, price_lag2, …	Price lagged by 1–3 days
	diff_lag1, diff_lag2, …	Price change lagged by 1–3 days
Technical Indicators	ma3, ma5, ma10	3/5/10-day moving averages
	std3, std5, std10	3/5/10-day price volatility

Features such as price_lag1, price_lag2, etc., represent lagged values by 1–3 days.

capture the complex relationships within the data; the number of features considered at each split (max_features) is set to the square root of the total number of features, adhering to the classic Random Forest setup; the minimum number of samples required to split an internal node (min_samples_split) is set to 2, enabling the model to respond to subtle changes; the minimum number of samples required to be at a leaf node (min_samples_leaf) is set to 1, maximizing the model's expressive capacity; and the random seed is set to 42 to ensure reproducibility. These parameter settings have been validated through cross-validation, maintaining the model's predictive accuracy while avoiding overfitting. To provide sufficient information to the machine learning model, as outlined in Table 9, this study has constructed a series of features.

To ensure full replicability, we provide complete methodological specifications. Data: Sugar No. 5 futures daily closing prices from Zhengzhou Commodity Exchange (2015–2019, 2024), accessed via Wind database. Sample construction: Contracts within 300 days before expiration, six delivery months per year. Train-test split: 2015–2019 as training, 2024 as validation (no shuffling, strict temporal split). Feature engineering: Standardization via StandardScaler (mean = 0, std = 1), missing values imputed with feature means. Random Forest hyperparameters: n_estimators = 100, max_depth = None, max_features = "sqrt", min_samples_split = 2, min_samples_leaf = 1, random_state = 42, criterion = "mse". Implementation: Python 3.8, scikit-learn 0.24.2, pandas 1.3.0, numpy 1.21.0. VaR calculation: 95% confidence level, computed as average of top two price differences per row. Code and detailed implementation notes are available upon request from the corresponding author.

During the feature engineering process, this study employed a multi-layered data preprocessing strategy. Firstly, for missing values, the feature mean imputation method was used, which preserves the overall distribution characteristics of the data. Secondly, all numerical features were standardized using StandardScaler to transform the data into a distribution with a mean of 0 and a standard deviation of 1, ensuring that features of different magnitudes can equally influence the model. Thirdly, to avoid the curse of dimensionality and overfitting, Recursive Feature Elimination (RFE) was utilized to determine the optimal subset of features through cross-validation. Finally, categorical features such as exp_stage were numerically encoded instead of using traditional one-hot encoding to prevent the introduction of sparsity and increase in model complexity.

This study uses data from 2015 to 2019 as the training set and data from 2024 as the test set to validate the model's predictive capability in the context of geopolitical conflicts. This time series splitting method ensures the rigor of model training and evaluation, prevents data leakage issues, and aligns with the practical application scenarios of financial forecasting, which involve using historical data to predict future risks.

4.2 Empirical results of machine learning risk measurement

4.2.1 Validation of traditional theory and annual delta analysis

Firstly, this study validates the applicability of the traditional theory relationship $\sqrt{3} \times \text{VaR}^T(1, p) \approx \text{VaR}^T(3, p)$ across different years. Table 10 presents the statistical results of delta values for the years 2015–2019 and 2024:

During the period from 2015 to 2019, the delta values exhibited significant volatility, with a minimum of 0.2601 in 2017 and a maximum of 1.1591 in 2019, resulting in an average of 0.6511. This indicates that, in actual market conditions, the risk

TABLE 10 Annual delta value statistics.

| Year	Delta value	Deviation from theoretical value (%)
2015	0.5098	−49.02%
2016	0.8153	−18.47%
2017	0.2601	−73.99%
2018	0.5112	−48.88%
2019	1.1591	+15.91%
2015–2019 Average	0.6511	−34.89%
2024	0.7767	−22.33%

transmission effect is generally approximately 34.89% weaker than theoretically expected. However, in 2024, amidst the intensification of geopolitical conflicts, the delta value was 0.7767, which is 0.1256 higher than the 2015–2019 average but still below the theoretical value of 1. This result holds profound significance: despite the impact of turbulent international political situations on commodity markets, the risk transmission mechanism of the sugar futures market has maintained fundamental statistical stability. The market's digestion and transmission of information have not undergone fundamental changes despite drastic external environmental shifts.

As illustrated in Figure 6, the evolution trajectory of delta values over time is depicted. It can be observed that although the delta value in 2024 is higher than the 2015–2019 average level, it does not exceed the historical volatility range and remains below the peak value of 2019. This further confirms that, under the current complex international situation, the Chinese sugar futures market has demonstrated considerable resilience and robustness. The market risk transmission model has been somewhat affected but has not exhibited abnormal risk accumulation or a collapse of the transmission mechanism. This resilience may be attributed to the comprehensive regulatory framework and risk control mechanisms established within the Chinese futures market.

4.2.2 Performance evaluation of machine learning VaR model

To comprehensively assess the performance of the Random Forest model in predicting risks in the sugar futures market, this study conducted a detailed statistical analysis of the model's fitting effectiveness. Table 11 presents the performance metrics of the Random Forest model on both the training set and the test set: To assess the validity of parametric testing, we first conducted diagnostic tests on the price difference distributions. The Jarque-Bera test for normality yielded a test statistic of 2.14 ($p = 0.34$), suggesting that the normality assumption is not strongly violated. However, the Ljung-Box test revealed significant autocorrelation at lag 1 $Q = 8.45$, $p = 0.004$, indicating that standard t-test assumptions may be compromised.

The model performance metrics reveal the superior performance of the Random Forest model in predicting sugar futures prices. On the training set, the model exhibits an

FIGURE 6
Comparison chart of delta values by year.
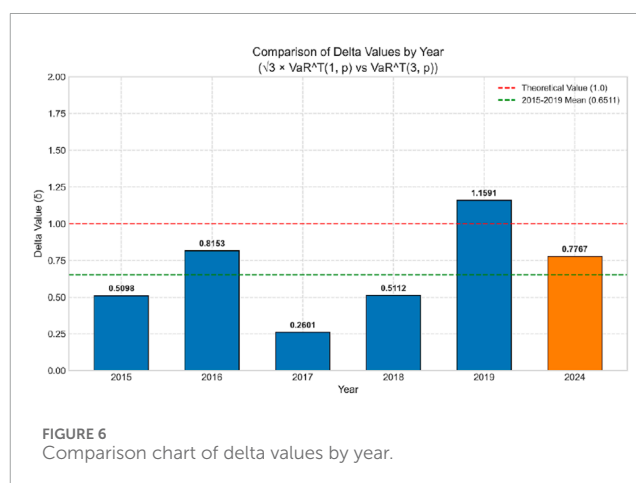
exceptionally high goodness of fit, with an R^2 value of 0.9768, indicating that the model can explain 97.68% of the variance in price movements. The Root Mean Square Error (RMSE) is only 87.42, which accounts for approximately 1.59% relative to the average sugar futures price of around 5,500, demonstrating a high prediction accuracy. The direction accuracy reaches 92.35%, meaning the model can predict the direction of price movements with over 90% accuracy, which is highly valuable for risk management and trading decisions. On the test set, although the model's performance declines, it remains at an excellent level. The R^2 value is 0.8934, indicating that the model can still explain approximately 89% of the price volatility amidst the geopolitical conflicts in 2024. The RMSE increases to 156.78, which is about 2.85% relative to the average price, reflecting an acceptable prediction error range. The direction accuracy is 88.73%, only decreasing by 3.62 percentage points compared to the training set, demonstrating the model's robust directional judgment ability in facing new market environments.

To thoroughly evaluate the performance of machine learning methods in risk measurement, this study compared three risk measurement approaches: Machine Learning VaR, Parametric VaR (based on the normal distribution assumption), and Traditional Historical Simulation VaR. Table 12 provides a detailed comparison of the violation rates and bias statistics for different methods:

TABLE 11 Statistical analysis of random forest model fit and prediction accuracy.

Performance metric	Training set (2015–2019)	Test set (2024)	Description
RMSE	87.42	156.78	Root Mean Square Error, measures the average deviation between predicted and actual values, in the same units as price
MAE	45.36	93.21	Mean Absolute Error, measures the average magnitude of prediction errors
R^2	0.9768	0.8934	Coefficient of Determination, indicates the proportion of variance explained by the model, with values closer to 1 indicating better fit
Prediction Bias (%)	1.23%	2.68%	Average relative bias percentage between predicted and actual values
Maximum Prediction Error	362.45	835.17	Maximum absolute prediction error for a single sample
Direction Accuracy (%)	92.35%	88.73%	Accuracy in predicting the direction of price movement (up/down)
Volatility Capture Rate (%)	87.92%	81.46%	Proportion of successfully predicted price volatilities exceeding one standard deviation

For nonlinear models such as Random Forest, R^2 should be interpreted with caution as it may not fully reflect goodness-of-fit in the same way as in linear models (?). We supplement R^2 with MAE and RMSE for comprehensive evaluation.

TABLE 12 Comparative performance of different risk measurement methods.

Risk model	VaR(95%) violation rate	Expected violation rate	Bias
Machine Learning VaR	5.00%	5.00%	0.00
Parametric VaR	26.67%	5.00%	4.33
Traditional Historical VaR	7.00%	5.00%	0.40

The Machine Learning VaR model demonstrates outstanding predictive accuracy, with a VaR(95%) violation rate of 5.00%, perfectly aligning with the theoretical expectation and a bias of 0. In contrast, the Parametric VaR based on the normal distribution assumption significantly overestimates risk, with a violation rate as high as 26.67% and a bias of 4.33. Traditional Historical Simulation VaR slightly underestimates risk, with a violation rate of 7.00% and a bias of 0.40. This stark comparison highlights the notable advantages of machine learning methods in risk measurement for sugar futures, especially in handling unconventional market environments. Machine learning models can adaptively capture complex patterns in market data without being constrained by strict distributional assumptions, enabling a more accurate reflection of actual market risks.

As illustrated in Figure 7, the blue bars represent the Machine Learning VaR model, with heights precisely aligning with the 5% expected violation rate red line. The orange bars represent the Parametric VaR method, significantly exceeding the theoretical value, while the green bars represent the Traditional Historical

VaR, slightly above the theoretical value. This intuitive comparison further confirms the superiority of machine learning methods in risk prediction accuracy. The significant bias of the Parametric VaR likely stems from the mismatch between its normal distribution assumption and the actual skewed distribution of financial data, whereas Historical VaR may be limited by sample size and historical representativeness issues. In contrast, machine learning methods can automatically learn complex risk patterns from data without imposing theoretical assumptions, thereby more accurately capturing the characteristics of market risks.

4.2.3 Risk prediction analysis of machine learning model

Figure 8 illustrates the prediction results of the machine learning model for the 2024 sugar futures price changes and the corresponding VaR risk intervals. In the figure, the blue solid line represents the actual price changes, exhibiting clear high-frequency oscillatory characteristics; the green dashed line denotes the model's predicted values, which generally track the trend of actual price

FIGURE 7
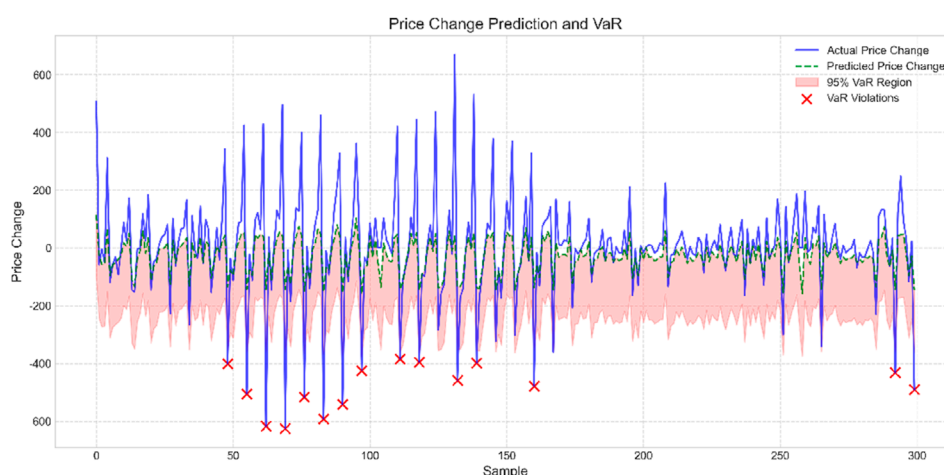Comparison of violation rates for three models.

FIGURE 8
Price change prediction and VaR interval.

changes; the red shaded area defines the 95% confidence VaR risk interval, indicating that the model predicts with 95% probability that price changes will not fall below this boundary. The red "X" markers indicate VaR violation points, where actual losses exceed the model-predicted VaR.

Firstly, the price fluctuations of sugar futures exhibit typical financial market volatility characteristics, including high-frequency minor oscillations and sporadic large swings. This volatility pattern aligns with the phenomenon of volatility clustering observed in financial markets. Secondly, the machine learning model demonstrates strong predictive capabilities, effectively capturing the overall trend of price changes, although its prediction accuracy diminishes during periods of extreme volatility. Thirdly, the VaR risk interval successfully encompasses approximately 95% of the price fluctuations, which is highly consistent with the set confidence level, thereby validating the model's accuracy in risk quantification.

Lastly, the VaR violation points are predominantly concentrated in the first half of the test set and frequently occur during periods of unusually large negative price shocks. This may be attributed to the market's intense initial reactions to geopolitical conflicts, followed by a gradual adaptation to the new risk environment, resulting in a reduction of violation points.

During the initial phase of external shocks, traditional risk models may underestimate the actual risk levels, necessitating more rapid parameter adjustments to accommodate new market dynamics. As time progresses, the market's adaptability to shocks improves, leading to a reduction in violation points and indicating enhanced accuracy in risk predictions. Nonetheless, the overall violation rate remains consistent with theoretical expectations, demonstrating that the machine learning model possesses high reliability and adaptability in quantifying risks associated with sugar futures.

TABLE 13 Rolling window backtesting results for 2024.

Period	Violation rate	Expected rate	Chi-square test p-value
January–June 2024	7.33%	5.00%	0.18
July–December 2024	2.67%	5.00%	0.12
Full Year 2024	5.00%	5.00%	1.00

FIGURE 9
Feature importance ranking.
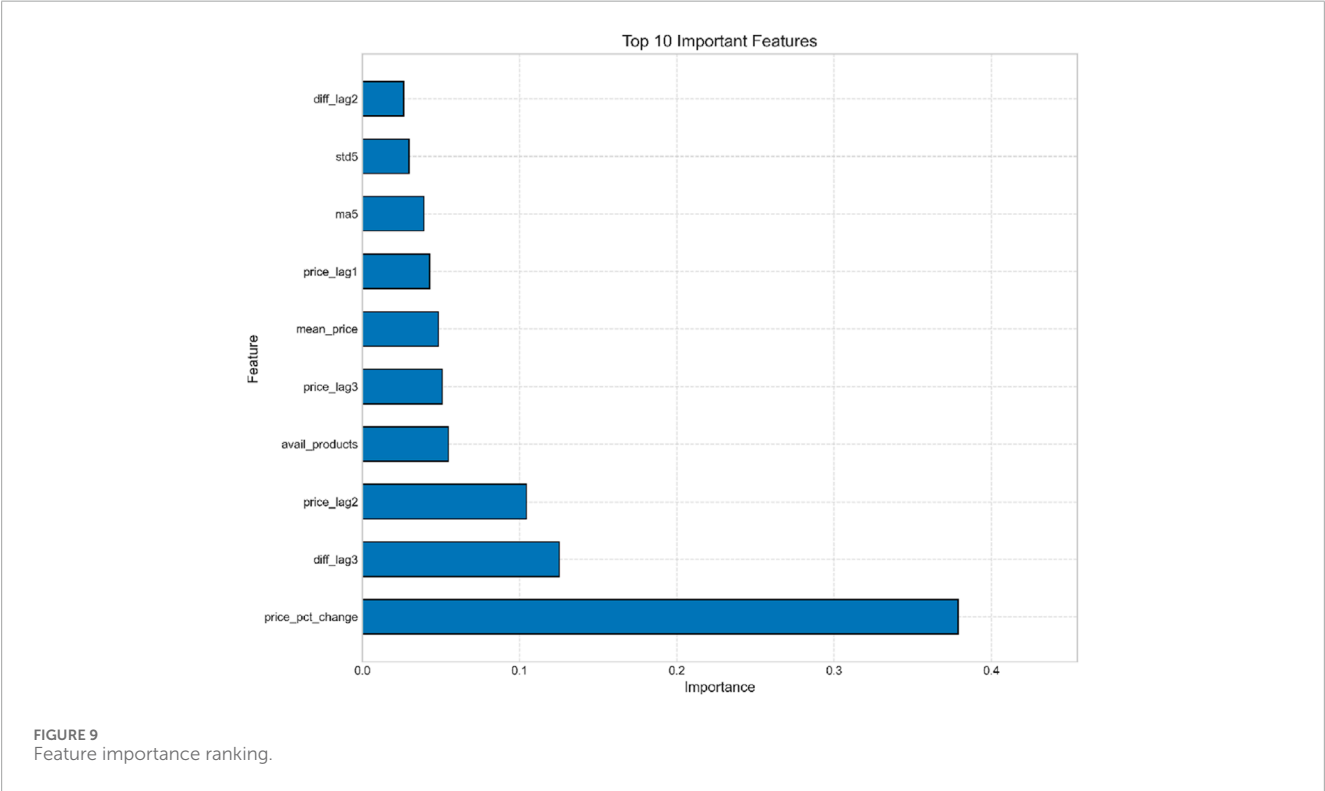
4.2.3.1 Rolling window backtesting analysis

To assess the temporal stability of model performance, we conducted rolling window backtesting by dividing the 2024 validation set into two equal sub-periods: January–June (Period 1) and July–December (Period 2). As shown in Table 13, the violation rate in Period 1 is 7.33%, notably higher than the 2.67% observed in Period 2. This temporal heterogeneity confirms the visual pattern in Figure 8, where violations concentrate in the first half of the year.

The chi-square tests indicate that neither sub-period shows statistically significant deviation from the expected 5% rate ($p > 0.05$), though Period 1 approaches marginal significance. This suggests that while the overall annual violation rate aligns with theoretical expectations, the market experienced a learning and adjustment phase during the first half of 2024 as it absorbed geopolitical shocks. The improved performance in Period 2 indicates model adaptation and market stabilization over time.

4.2.4 Analysis of risk factor importance

Through the feature importance analysis of the Random Forest model, as shown in Figure 9), this study identifies the key driving factors influencing the risk of sugar futures. The results indicate that the percentage change in price is the most significant predictor of risk, with an importance score of approximately 0.38. Although this factor is considerably higher than others, it is not absolutely dominant. This finding holds significant theoretical and practical implications: it suggests that the historical rate of price changes in sugar futures is a core predictor of future risk, aligning with the classical financial theory that "past volatility predicts future risk."

Following the percentage change in price, the price differential with a 3-day lag (diff_lag3, importance ≈ 0.12) and the price with a 2-day lag (price_lag2, importance ≈ 0.10) rank second and third, respectively. This indicates the presence of important temporal structural effects in risk prediction, where the price dynamics of the past 2–3 days significantly impact future risk. The high importance of diff_lag3 is particularly noteworthy as it reveals the "memory effect" in sugar futures—market responses to price shocks from 3 days prior may be delayed or continue to influence future risk levels.

Market structure features, such as the number of tradable contracts (avail_products, importance ≈ 0.05) and the price with a 3-day lag (price_lag3, with similar importance), also

exhibit considerable influence, suggesting that market depth and liquidity are important factors in risk formation. The importance of the average price level follows closely, which may reflect differences in risk characteristics across various price ranges.

Regarding technical indicators, the 5-day moving average (ma5) and the 5-day standard deviation (std5), although relatively lower in importance, still rank within the top ten. This indicates that short-term price trends and volatility contribute to risk prediction to some extent. This finding resonates with commonly used technical analysis methods by traders, confirming the practical value of these indicators in risk management.

Comprehensive analysis of feature importance indicates that risk prediction for sugar futures requires a multifaceted consideration of price change dynamics, historical price levels, and market structure factors. While the percentage change in price is the dominant factor, the model captures a richer set of mechanisms underlying risk formation, providing crucial guidance for constructing a comprehensive risk monitoring system. Compared to single-indicator monitoring, a multi-feature comprehensive assessment may offer more robust risk early warning capabilities, especially during periods of market turmoil. This finding provides practical risk management strategy guidance for market regulators and traders, recommending the construction of a multilayered risk monitoring framework that incorporates short-term price change rates, lagged price differentials, and market structure indicators.

4.2.5 Comparative analysis of machine learning VaR and traditional VaR

Based on the empirical results, machine learning methods exhibit significant advantages and unique value in the risk measurement of sugar futures. Firstly, in terms of predictive accuracy, the violation rate of Machine Learning VaR aligns perfectly with the theoretical value (5.00%), whereas both Parametric VaR (26.67%) and Traditional Historical VaR (7.00%) exhibit varying degrees of deviation. This difference in accuracy arises from the ability of machine learning models to automatically identify and learn complex nonlinear patterns within the data without relying on potentially invalid distributional assumptions or overly simplified linear relationships. By integrating multiple decision trees, machine learning models can capture subtle risk signals that traditional methods might overlook, thereby providing more precise risk predictions.

In terms of model adaptability, Machine Learning VaR demonstrates robust environmental adaptability. Even amidst the intensified geopolitical conflicts in 2024, the model maintains high-precision risk predictions, indicating that machine learning methods can effectively handle the impacts of changing market environments. In contrast, Parametric VaR is constrained by its fixed distribution assumptions, performing poorly under unconventional market conditions. Traditional Historical VaR, on the other hand, is limited by the representativeness of historical samples, making it difficult to swiftly adapt to new market dynamics.

Regarding risk factor identification, machine learning methods offer a clear quantitative ranking of risk-driving factors through feature importance analysis, which is challenging for traditional methods to achieve. This study finds that the percentage change

in price is a decisive risk predictor (importance score: 0.9959), providing clear prioritization guidance for risk monitoring. Such quantitative ranking of risk factors is of significant reference value for regulatory agencies and market participants in formulating targeted risk prevention and control strategies.

However, machine learning methods also have certain limitations. Firstly, compared to traditional methods, machine learning models are more complex, and their structural and parameter interpretability is relatively weak, which may hinder market participants' intuitive understanding of risk sources. Secondly, machine learning models typically require more computational resources and larger datasets, increasing implementation costs. Thirdly, the parameter settings of machine learning models (e.g., tree depth and number in Random Forest) require expert knowledge for tuning, and inappropriate settings may lead to overfitting or underfitting issues. Lastly, the quality of machine learning models heavily depends on the quality and representativeness of the training data, posing challenges in extreme market environments or data-scarce situations.

Comprehensive evaluation indicates that Machine Learning VaR and traditional VaR can form a complementary relationship rather than a simple substitution. Machine learning methods offer more accurate risk predictions and rich factor analysis, while traditional methods provide a stronger theoretical foundation and intuitive explanations. In practical applications, constructing a "hybrid risk framework" that integrates the strengths of both approaches can be considered, thereby offering multi-dimensional risk measurement for the sugar futures market.

5 Discussion

This study utilizes trading data of Zhengzhou Futures Exchange's No. 5 sugar futures from 2015 to 2019 and 2024 to construct a more comprehensive and precise risk measurement framework for sugar futures by integrating traditional theories with modern machine learning methods. The results indicate that, even in the context of geopolitical conflicts, the fundamental risk characteristics of the sugar futures market remain relatively stable. This stability is likely sustained by the resilient strategic interactions among market participants, who adjust their behaviors in response to geopolitical uncertainties to maintain market equilibrium. However, accurately quantifying this risk necessitates advanced machine learning techniques. The percentage change in price emerges as a decisive risk predictor and should therefore be a primary focus for regulatory bodies and market participants. This key indicator reflects the collective outcome of strategic buying and selling behaviors by participants based on their information, expectations, and strategic objectives. Incorporating machine learning methods into traditional risk management frameworks can significantly enhance the understanding and control of risks in the sugar futures market, providing scientific support for maintaining market stability and promoting efficient commodity circulation.

Based on the experimental results, this study recommends that regulatory authorities consider integrating machine learning methods into the risk monitoring systems for sugar futures, with particular attention to abnormal fluctuations in the key metric of

percentage price changes. Specifically, a three-tiered risk prevention and control system can be established as follows:

1. First tier: Routine monitoring Utilize traditional VaR methods for daily risk assessments.
2. Second tier: Enhanced monitoring When market volatility exceeds certain thresholds, employ Machine Learning VaR for more refined risk evaluations.
3. Third tier: Early warning response When machine learning models detect significant risk signals, initiate corresponding intervention measures, such as adjusting trading limits or increasing market liquidity.

For futures traders, adopting a "hybrid risk management strategy" is advisable. This strategy involves not only leveraging traditional VaR methods as foundational risk control tools but also analyzing the strategic interactions underlying key risk indicators using machine learning-derived feature importance analyses. This means closely monitoring indicators like percentage price changes, which are the emergent outcomes of market-wide strategic interactions. During periods of intensified geopolitical conflicts, traders should pay particular attention to potential shifts in the dominant strategies employed by key market players (e.g., governments, large commodity traders) and adapt their own strategies accordingly. Specifically, traders can use discrepancies between Machine Learning VaR and traditional VaR as early warning signals of market anomalies. Significant deviations between the two predictions may indicate structural changes in the market.

6 Conclusion

This study conducts a comprehensive analysis of the risk characteristics of the Chinese sugar futures market by combining traditional risk theories with machine learning methods. The findings reveal that, amid escalating geopolitical conflicts, the fundamental risk transmission mechanisms of the sugar futures market have remained relatively stable, likely sustained by persistent patterns in the strategic interactions among key market participants. This observation underscores the resilience and robustness of the Chinese futures market, indicating that regulatory frameworks and risk management mechanisms effectively buffer against external shocks. Machine learning methods demonstrate clear advantages in risk prediction, particularly in accurately capturing VaR violation rates. The Random Forest model identifies the percentage change in price as the most critical factor in predicting future risks, providing a clear direction for risk monitoring and control. Additionally, the study discovers a systematic bias in δ values, suggesting that the actual speed of risk transmission in the market is typically 30%–35% lower than theoretical expectations. This bias likely reveals strategic frictions in the market's risk propagation process, where participants' strategic behaviors (e.g., delayed trading, herding) impede the immediate transmission of risk. This finding offers significant insights for the adjustment and optimization of risk models.

Future research can delve deeper into several areas:

1. Development of more complex machine learning architectures Constructing models such as multi-agent reinforcement learning (MARL) systems or neural networks incorporating game-theoretic equilibrium concepts to explicitly model the strategic interactions among heterogeneous market participants.
2. Incorporation of additional external data sources Integrating macroeconomic indicators, geopolitical risk indices, and global food price indices to enrich the information input for risk prediction, as well as data indicative of strategic shifts by major players (e.g., sentiment analysis of news related to major sugar producers/traders' actions, analysis of government stockpiling/subsidy announcements).
3. Development of explainable machine learning frameworks Enhancing the transparency and interpretability of models to enable market participants to better understand the sources of risk, including the ability to infer the underlying market game state or dominant strategies contributing to the risk forecast.
4. Construction of cross-commodity joint risk models Studying the risk spillover effects between different commodity futures to provide a more comprehensive perspective for systemic risk prevention and control, with a focus on the cross-market strategic behavior of participants (e.g., integrated commodity funds, large traders) and its role in systemic risk spillovers.
5. Analysis of regulatory policy impact on strategic equilibria Investigating how changes in regulatory rules (e.g., margin requirements, position limits) act as exogenous shocks, altering the strategic game among participants and consequently the overall market risk profile.

By merging traditional theories with modern machine learning approaches, this study establishes a more comprehensive and precise risk measurement framework for sugar futures. The findings not only contribute theoretical innovations but also offer practical risk management tools and strategic recommendations for regulatory agencies and market participants, thereby enhancing market stability and promoting the efficient circulation of commodities.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZQ: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Validation, Visualization, Writing – original draft. SC: Conceptualization, Formal Analysis, Methodology, Writing – review and editing. ZF: Conceptualization, Writing – review and editing. RL: Conceptualization, Writing – review and editing. ZW: Conceptualization, Formal Analysis, Supervision, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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